Oil Prices, Fundamentals and Expectations

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April 19, 2018

Abstract

This paper empirically investigates the relationship between oil prices, traditional fundamentals and expectations. Informational frictions may force a wedge between oil prices and supply and/or demand shocks, especially during periods of elevated risk aversion and uncertainty. In such a context, expectations can be a key driver of oil price movements and their impact can vary over time. Overall, we find that both traditional oil fundamentals and forward-looking expectations matter for oil prices. Our findings show that the real price of oil responds differently to expectations shocks of business leaders, consumers and aggregate markets. Our TVP-VAR approach provides evidence that business leaders' expectations play an important role in terms of oil price fluctuations and the impact is stronger in periods of elevated global oil demand. In terms of traditional oil market fundamentals, we find that oil prices have been significantly affected by the recent US shale oil boom. Moreover, global oil demand had a positive impact upon oil prices, especially from the mid-2000's. Several alternative model specifications prove the robustness of our analysis.

Keywords: Crude Oil Prices; Informational Frictions; Fundamentals; Expectations; Time-Varying Parameters.
JEL classification: C30, E30, F00, Q43.

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1 Introduction

Oil is a core source of energy for the global economy and essential for economic activity. Changes in oil prices can be rapid, and large price swings severely impact commodity importers, exporters and speculators. For example, higher oil prices may lead to lower aggregate demand and production outputs, induce inflationary tendencies and higher interest rates for importing countries; whereas a sustained decline in oil prices supports the so-called "resource curse" hypothesis for commodity abundant emerging economies.[1] Thus, a better understanding of the nature of oil prices and their determinants are crucial for policymakers and the private sector, and may lead to better decision making in areas such as macroeconomic policy, risk and portfolio management (Xu and Ouenniche, 2012).

The recent economic literature has contributed substantially to a better understanding of the causes of oil price fluctuations since the 1970's. Traditionally, oil price fluctuations were thought to reflect unexpected changes in oil supply, such as production disruptions due to conflicts and co-ordinated supply constraints in producing nations.[2] Subsequent research has argued that supply factors were only one among many explanations and less important than previously believed.[3] In an innovative paper, Kilian (2009) has disentangled the effects of demand and supply side shocks underlying the evolution of the real price of oil. He found that, since 1973, major changes in oil prices were primarily driven by demand factors. These factors included shifts in global demand for industrial commodities and unanticipated increases in precautionary demand for crude oil.

Supply and demand fundamentals are clearly important. However, recent papers have considered whether market participants directly observe these fundamentals. In particular, Sockin and Xiong (2015) highlighted that the presence of severe informational frictions could lead to confusion among market participants about the strength of the global economy and oil demand relative to supply. Therefore, it may be unrealistic to as-

[1]See among the others, Lu and Neftci (2008); Frankel (2014); Baumeister and Kilian (2016).

[2]See Hamilton (2003), and Jones et al. (2004).

[3]See the literature from Lippi and Nobili (2012), Baumeister and Peersman (2013a), Abhyankar et al. (2013) and Kilian and Murphy (2014).

sume that producers and consumers can directly and contemporaneously observe whether oil prices are fully consistent with actual fundamentals. Without a contemporaneous link between oil prices and fundamentals, the role of expectations becomes crucial. In this regard, the findings by Singleton (2014) highlighted the importance of accounting for agents' expectations in explaining the commodity market boom-bust cycles.

Our paper extends the literature on identifying the determinants of oil prices by incorporating economic agents' expectations on the state of the global economy. This issue relates specifically to informational frictions but more generally to research in behavioural finance and psychology, which argues that moods and emotions affect individuals' behaviour and aggregate prices and quantities (see, for example, Akerlof and Shiller, 2009; Gino et al., 2012; Garcia, 2013). However, this topic has not been extensively investigated in relation to oil prices. In our paper, we account for a range of confidence and leading indicators which provide a broader perspective of the overall economic outlook. Global survey-based confidence indicators shall therefore be adopted in this study as a gauge the state of the global economy in the presence of informational frictions.[4]

There are several important reasons why it is important to investigate the role of expectations in the oil market. First, although supply and demand factors of the fundamental cause of oil price fluctuations, expectations may be the proximate cause of their movements. Second, expectations account for informational frictions and departures from the oil price suggested by fundamentals (Sockin and Xiong, 2015). Third, expectations also account for the idea that oil prices exhibit forward looking behaviour, which can augment measured demand especially at turning points in the economic cycle. Furthermore, expectations are frequently emphasized in economics research, for example, the New-Keynesian Phillips curve literature considers the importance of fundamentals and forward-looking behaviour in a goods price setting (Gali and Gertler, 1999; Byrne et al., 2013). Finally, expectations encompass the idea that there has been increased financialization of oil, since investors shall seek to maximise expected returns based upon asset

[4]See, for example, Carroll et al. (1994), Bram and Ludvigson (1998), Ludvigson (2004), Bachmann and Sims (2012), Christiansen et al. (2014) and Caglayan and Xu (2016).

prices (Cheng and Xiong, 2014).

Given these arguments, the central contribution of this paper is to investigate the impact of expectations upon oil prices. More specifically, we use three different expectational proxies for OECD countries: business confidence, consumer confidence and market leading indicators. These three measures capture the expectations on future global economic outcomes from business leaders, consumers and aggregate markets, respectively. Even though these expectations may be interrelated and contemporaneous, business leaders, consumers and markets can act on a specific set of (imperfect) information that emanates from the state of the economy, rational inattention or the agent's own asymmetric goals and strategies. Figure 1 illustrates that, while there are similarities between these sources of expectations, they do evolve differently over time. Therefore, it is important to find out how oil prices would respond to variations in different economic agents' expectations on the state of the economy and we do this in our empirical study analysing the relationship between oil prices, fundamentals and expectations.

While the focus of this work is upon expectations and oil prices, a second contribution of this paper is to note that there are reasons to believe the impact of determinants upon oil prices may be time varying and we should adopt a methodology sufficiently flexible to account for this. For example, China has significantly increased its market shares of global commodities following its rapid development affecting world demand (Kilian, 2009; Frankel, 2014). Financial investors' risk-bearing appetite and the risk premium can vary over time (e.g., Acharya et al., 2013; Cheng and Xiong, 2014). There is also time-dependent volatility in world oil production (e.g., Baumeister and Peersman, 2013a; Baumeister and Peersman, 2013b). Importantly, informational frictions may themselves change over time, also leading to a decoupling of oil prices and fundamentals in periods of acute uncertainty about the global economy. These characteristics imply a time-varying relationship between the underlying drivers and oil prices.[5] Therefore, to carry out our investigation, we use a time-varying vector autoregression (TVP-VAR) model

[5]See, for example, Peersman and Van Robays (2012), Millard and Shakir (2013) and Baumeister and Peersman (2013a).

with stochastic volatility model to simultaneously model the evolving roles of both oil market fundamentals and expectation shocks on oil prices for the period between 1974 and 2016.

Our estimated results show that oil prices respond to both traditional fundamentals and heterogeneous economic agents' expectations over time. In particular, we find that the real price of oil responds differently to expectations that arise from business leaders, consumers and aggregate markets. In this regard, shocks to business leaders have the most important role in explaining oil price movements and increases in business leaders' expectations have a large and positive impact upon the real price of oil although this effect is very time-dependent. Optimistic business leaders' expectations coincide with stronger oil demand and, in turn, induce a higher real oil price. Such a result is explained by the fact that business leaders are generally well informed about prospects for the economy. In contrast, our findings indicate that consumers' confidence plays a negligible role in terms of oil price fluctuations. In particular, our variance decomposition shows that consumers' expectations contribute less than 2% of oil price variation one year after the shock occurs.

In terms of traditional oil market fundamentals, our estimated results show that the recent US shale oil boom had a strong negative effect on the real oil price. Finally, we find that, since the middle of the 2000's, oil prices responded positively and strongly to unexpected increases in demand, possibly due to increased demand for industrial commodities from many emerging market economies.

The rest of the paper is organized as follows. Section 2 formally presents our econometric methodology and Section 3 discusses the data. Section 4 reports the empirical results and robustness checks. Section 5 offers some concluding remarks.

2 Empirical Methodology

In this section, we present our empirical model that builds on the structural VAR analysis of the real oil price proposed by Kilian (2009). As an extension of the framework provided by Kilian (2009), we also include expectations of different economic agents as we discuss below. Following Peersman and Van Robays (2009) and Peersman and Van Robays (2012), we adopt the Bayesian technique for estimation and inference. As it is well known, the Bayesian approach has two main advantages. Firstly, it is computationally simple. Secondly, it provides a conceptually clean way of drawing error bands for impulse responses from VAR models (Peersman and Van Robays, 2012). Finally, we account for time-varying parameters (TVP) in order to examine the determinants of oil prices. The TVP-VAR model with stochastic volatility allows us to understand how changes in oil market fundamentals and economic expectations affect the real oil price over time.

Our basic VAR model can be written as follows:[6]

$$A_0 Y_t = \Sigma_{i=1}^{p} \Gamma_i Y_{t-i} + u_t, t = p+1, ..., T \tag{1}$$

where Y_t is a $K \times 1$ vector of endogenous variables including the changes in the global oil production ($\Delta prod_t$), an index of global real economic activity (rea_t), the changes of economic agents' expectations (Δexp_t), and the real price of oil (rpo_t). Γ_i denotes a $K \times K$ matrix of coefficients, A_0 indicates a $K \times K$ matrix of contemporaneous coefficients of Y_t, and u_t denotes the vector of serially and mutually uncorrelated structural shocks. The lag length is set to two (i.e. $p = 2$).[7]

In order to orthogonalize the shocks, we impose a recursive structure on the contemporaneous terms and assume exclusion restrictions on A_0^{-1}. In particular, the structural

[6] In Appendix A, we provide the full derivation for both the constant parameter Bayesian VAR and the time-varying parameter Bayesian VAR with stochastic volatility.

[7] Most lag length specification tests (e.g., Final Prediction Error; Akaike Information Criterion; and Hannan-Quinn Information Criterion) suggest that two lags should be included for our model with quarterly data.

shocks u_t are identified by decomposing the reduced-form errors ε_t as follows:

$$\varepsilon_t \equiv \begin{pmatrix} \varepsilon_t^{\Delta prod_t} \\ \varepsilon_t^{rea_t} \\ \varepsilon_t^{\Delta exp_t} \\ \varepsilon_t^{rpo_t} \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix} \begin{pmatrix} u_t^{supply} \\ u_t^{demand} \\ u_t^{exp} \\ u_t^{res} \end{pmatrix} \tag{2}$$

As we can observe from equation (2) we assume four structural shocks that drive the real price of oil. Firstly, u_t^{supply} reflects an unexpected shift of global oil supply. These are not driven by changes in the macroeconomic environment, but due to exogenous production disruptions due to political instabilities, wars or changes in production quotas set by the OPEC members. Secondly, u_t^{demand} captures the shift in the demand for all industrial commodities including crude oil that is associated with unexpected fluctuations in the global business cycle, such as the unexpected strong demand from emerging economies. Next, u_t^{exp} reflects the variations of specific economic agents' (i.e., consumers, business leaders, and markets) expectations about future economic conditions. These expectations proxy agents' sentiment about future economic trends. Sentiment may vary based upon elevated risk or uncertainty in financial markets, as in the global financial crisis. Finally, u_t^{res} denotes the residual shock that captures idiosyncratic oil demand shocks not otherwise accounted for.[8]

As we explained above, we estimate the VAR model with Bayesian methods.[9] In particular, we adopt the independent Normal-Wishart prior, which is more flexible than the natural conjugate prior. Following Primiceri (2005), we use a training sample prior that corresponds to the first 40 observations (1974:Q4 to 1984:Q3). Using the Markov Chain Monte Carlo (MCMC) method, 100,000 samples are obtained after the initial 30,000 samples are used as burn-in and discarded.

[8]In Appendix A, we describe in detail the restrictions on A_0^{-1} that are based on economic intuitions.

[9]All estimations are implemented with Matlab R2014B (https://www.mathworks.com/products/matlab.html).

3 Data

To carry out our investigation we use quarterly data and our sample period begins in 1974:Q4 and ends in 2016:Q1. In Table 1, we present the sources and definitions of the data used in this study. First of all, we use the percentage change of oil production ($\Delta prod_t$) obtained by the log differences of world crude oil production in millions per barrels pumped per day (averaged by quarter). This data is obtained from the Energy Information Administration (EIA). Secondly, as a proxy for global economic activity (rea_t) and following Kilian (2009) we use a measure constructed from an equal-weighted index of the percent growth rates of a panel of single voyage bulk dry cargo ocean shipping freight rates measured in dollars per metric ton.[10] The rationale behind using this proxy is that increases in shipping rates reflects changes in the global demand for industrial commodities, including that of emerging countries such as China and India, given that supply of ocean-going vessels is likely to be inelastic in the short-run.

Regarding our measures of economic agents' expectations (Δexp_t), we extract standardized and amplitude adjusted business confidence indicators, consumer confidence indicators, and composite leading indicators for all OECD countries from the "OECD Main Economic Indicators" database. The main advantage of utilising composite indicators from the OECD is that they apply the same criteria to construct their indicators across countries, so that they are consistent and comparable. Firstly, we use the OECD's Business Confidence Index (BCI) as a proxy for business leaders' expectations. This indicator combines a set of business tendency survey variables (e.g., the current and immediate future expectations on production, orders and stocks) into a single composite indicator that summarizes managers' assessment and expectation of the general economic situation. To capture consumers' expectations, we make use of the OECD's Consumer Confidence Index (CCI). CCI is based on information collected from consumer opinion surveys regarding the households' intensions for major purchases, their current economic

[10]Data used in Kilian (2009) is available from Lutz Kilian's homepage. The reader is referred to Kilian (2009) for details on the construction of this index.

state as compared to the recent past and their expectations for the immediate future (i.e., three months). The main characteristic of the business and consumer surveys is that they ask for the direction of change by referencing to a normal state. In translating these qualitative results into a time series, only the balance is shown by taking the difference between percentages of respondents giving favourable and unfavourable answers. Both BCI and CCI are expressed as an index (normalised at 100) and they are seasonally adjusted. In addition, we use the Composite Leading Indicator (CLI) to capture the aggregate perception of the business leaders and consumers on the economic outlook. CLI is an aggregate time series which comprises a set of component series selected from a wide range of key short-term economic indicators. Although the underlying component series can be different for different countries depending on their economic significance, cyclical behaviour, data quality, timeliness and availability for the specific country, the CLI is designed to capture turning points and moves in the same directions as the business cycle.[11]

Our measure of the real oil price (rpo_t) is based on the Europe Brent spot price FOB which is expressed in US dollars per barrel. We use this series as the relevant crude oil price for the world economy.[12] The monthly series of the Brent crude oil price obtained from the Datastream database is aggregated in quarterly terms and deflated using the US consumer price index. Figure 2 depicts the behaviour and dynamics of the price of Brent crude for the sample period 1985-2016. The graph shows that the oil price can be sensitive to different shocks including changes in global crude oil production, unexpected changes in global macroeconomic conditions, unexpected strong demand for oil from emerging markets and the global financial crisis (e.g., Abhyankar et al., 2013; Kilian, 2008; Kilian, 2016).

[11] For detailed component series for each country, the reader is referred to the OECD Leading Indicators webpage.

[12] In the robustness checks section, we present the estimated results of our model using the US refiner acquisition cost of imported crude oil; this does not qualitatively change our main conclusions.

4 Empirical Discussion

In this section, we examine the relationships between oil price shocks, oil market fundamentals and economic agents' expectations. Before presenting our estimated results, we describe the intuition behind the link between oil price changes and agents' expectations.

4.1 Economic Agents' Expectations and Oil Price Fluctuations

The previous economic literature has shown that there are several channels through which physical oil demand can be potentially affected. Kilian and Murphy (2014) found that the speculative channel played an important role during the oil price shock episodes of 1979, 1986, and 1990. More recently, the study by Gao et al. (2017) highlighted the role of precautionary inventory stocks. In our paper we focus on an alternative channel, that is, economic agents' expectations. In particular, we aim to investigate whether the expectations' channel is able to affect the physical oil demand in the oil spot market.

Our idea is based upon the work of Sockin and Xiong (2015) arguing that economic agents face severe informational frictions about the main mechanisms driving the oil market. The globalization of crude oil exposes market participants to informational frictions regarding its supply and demand. Aggregating such information from different countries is challenging. Moreover, there may be incomplete public information on the supply and inventory of crude oil, as it incorporates both above-ground, below-ground and ship-board supply. Based on these facts Singleton (2014) argued that heterogenous beliefs can lead market participants to engage in speculative trading against each other, which, in turn, may induce commodity prices to drift away from fundamental values, and result in price surges and plunges.

Severe informational frictions can lead to confusion among market participants about the strength of economies. When business leaders are fearful about the future economic outlook they can decrease their demand for oil and affect its price negatively. On the other hand, unanticipated positive shocks to expectations due to positive policy intervention and strong emerging market demand can lead to a higher oil demand and, ultimately, a higher price of oil.

Moreover, Sockin and Xiong (2015) have shown that when goods producers face unobservable shocks to oil demand and supply standard economic intuitions may not hold. For example, due to informational frictions, oil demand may rise with an increase in oil prices. Confident expectations of business leaders may affect positively oil demand and, in turn, induce an increase in the real oil price. On the other hand, business leaders may not able to affect oil prices through the oil supply channel. To be more specifically, firms' leaders cannot differentiate an oil price decrease caused by a positive supply shock from an oil price decrease caused by a negative demand shock in the presence of informational frictions. Hence, they partially attribute the supply shock to the demand shock.

All things considered, the discussion makes clear that economic agents' expectations are important for oil price fluctuations. Therefore, in the following subsection we present the impulse response functions of oil prices based upon a standard Bayesian VAR (BVAR) model. Thereafter, we investigate whether the VAR model is robust to time variation based upon findings from our TVP-VAR model.

4.2 Fundamentals and Expectations from a BVAR Model

Using our Bayesian VAR model, Figures 3 to 5 depict the impulse responses of oil prices to oil supply, aggregate demand and expectations shocks over the full sample and two sub-sample periods corresponding to 1974:Q4-1998:Q4 (S1) and 1999:Q1-2016:Q1 (S2), respectively. Our sample split relates to the pattern of oil prices showing a moderate volatility of this series in S1 whereas, evidently, during S2 sharp changes to oil prices have occurred (see for example, Baumeister and Peersman, 2013a). We present our results for a ten quarter response horizon. Our responses include the posterior median as the solid line, while the dashed lines are the $16th$ and $84th$ percentiles of the posterior distribution.[13]

We start by discussing the impulse responses functions (IRFs) of oil prices to oil market fundamentals and business leaders' expectation shocks (see Figure 3). The estimated results for the full sample period are shown in the first row. As we can see, an increase in oil production does not affect oil prices substantially since the zero axis is within the 68% posterior credible interval. On the other hand, we find that the demand shocks have larger and more persistent long-term effects. To be more specific, aggregate demand shocks caused by unexpected increases in global demand for all industrial commodities lead to a persistent and significant increase in the real price of oil. The response reaches its peak after two quarters and stabilizes soon after that. Our findings are consistent with previous studies such as Kilian (2009) and Abhyankar et al. (2013) who also find that supply, as compared to aggregate demand, played a less important role on average in explaining oil price movements.

Furthermore, as we can see from the top right graph in Figure 3, a positive shock from business leaders' expectations about the future economic conditions causes an immediate increase in the real price of oil. Our findings are consistent with previous literature in other contexts showing that survey-based sentiment indicators contain additional information on the state of economy which is not already available in other standard economic indicators (e.g., Ludvigson, 2004; Christiansen et al., 2014).[14] The second and third rows of Figure 3 display the median impulse responses of oil prices to oil supply, aggregate demand and expectations shocks for sub-samples S1 and S2. In general, we observe an evolving relationship between the real price of oil, oil market fundamentals and managers' expectations. For example, we find that the aggregate demand shocks and expectation shocks played more important roles during the second sub-sample period as compared to the first sub-sample period.

[13] Under normality, the $16th$ and $84th$ percentiles correspond to the bounds of one-standard deviation (Primiceri, 2005).

[14] In addition, based on regression analysis, Deeney et al. (2015) and Han et al. (2017) found that market-based investor sentiment and text-based investor attention proxies provide significant forecasting power to predict oil prices, respectively.

Given that we are interested in examining whether oil prices respond differently to several economic agents' expectations, now we replace the business confidence indicator in our BVAR model with the consumer confidence indicator and composite leading indicator over the full sample and the two sub-samples S1 and S2 (see Figures 4 and 5). As we can observe from the first and second columns of Figures 4 and 5, the responses of oil prices to supply and demand shocks are similar to those in Figure 3. However, changes in consumers' expectations with regards to future economic conditions play a less important role as compared to business leaders' expectations. This may be explained by the fact that business leaders are generally better informed about the prospects of the economy than consumers, because they focus on investment prospects and future profitability which are affected by a large number of factors and have greater access to market information. The top right graph of Figure 5 gives the impact of aggregate markets expectations from our OECD composite leading indicator (CLI). Raised expectations of the state of the economy induce a positive rise in oil prices. In addition, when we split our samples into two sub-periods, our estimated results indicate that the relationship between the real price of oil, oil markets' fundamentals and economic agents' expectations have evolved over time (see the second and third rows of Figures 4 and 5). This motivates the use of a TVP-VAR which firstly does not assume the impact of fundamentals and expectations are constant over time, and secondly, does not require us to exogenously fix sub-samples.

4.2.1 Variance Decomposition Analysis

Now, we turn to the evaluation of the shocks affecting oil price fluctuations. More specifically, Table 2 (Panels (*i*), (*ii*) and (*iii*)) reports the variance decomposition of the real oil price for our three models including both oil market fundamentals (i.e., oil supply and demand shocks) and expectations (i.e., business leaders, consumers, and markets). In addition, Panel (*iv*) reports the results when we only include oil market fundamentals as in Kilian (2009). Residual shocks and aggregate demand shocks are the most important fundamentals for oil price variation. Importantly, we find that expectations of future economic conditions make a significant contribution in explaining the variation of the real oil price. When we proxy expectations by confidence from business leaders in Table 2, Panel (i), BCI shocks have the largest impact upon oil prices (around 16% after four quarters). Moreover, we note that the contribution of BCI shocks to oil price variation is more than twice as large as oil supply shocks. Consumers' expectations are relatively less important for oil price variability in Table 2, Panel (ii). Consumers' expectations explain less than 2% of the variation of oil prices after four quarters. The results for the third proxy of expectations (i.e., CLI shocks) are provided in Panel (iii) of Table 2. CLI shocks explain almost around 8% of the variability in oil price changes one year after the shock occurs. Finally, we turn to the model excluding expectations. Over longer horizon, more than 48% of variation in the real price of oil is driven by residual shocks in Panel (iv). On the contrary, in our model including business leaders' expectations, residual shocks account for only 35% of the variation over the longer horizons. This indicates that expectations can substantially, albeit not completely, fill the information gap in the oil market. To conclude, our findings highlight the relative importance of residual, aggregate demand, supply and business leaders' expectations shocks in explaining oil price movements.

4.3 TVP-VAR Model with Stochastic Volatility

In this section, we focus upon the time evolution of the relationship between the real price of oil, global oil production, aggregate real economic activity and expectations using a TVP-VAR model with stochastic volatility. Such an approach allows us to consider the evolving impact of oil market fundamentals, as well as expectations which may be important when there are heightened informational frictions.

4.3.1 Response of Oil Price to Traditional Oil Market Fundamentals

We begin our time-varying analysis by highlighting that the response of oil prices to traditional fundamental shocks is robust, irrespective of the measure of expectations. Figures 6-8 show the contemporaneous time-varying impulse responses of oil prices to positive shocks in oil supply and aggregate demand. In these figures the posterior median is the solid line and the dashed lines are the 16*th* and 84*th* percentiles of the posterior distribution. We plot the reaction of the real price of oil for the quarter in which the shock occurs. First, we find that positive innovations to global oil supply have a consistently negative impact on the real price of oil (see top panels of Figures 6-8). The effect of oil supply shocks on the real price of oil is evidently time-varying as we observe a smaller response during the 1990's and 2000's as compared to the early years of our sample. Recently with the impact of the US oil shale revolution, the negative effect of oil supply shocks on the real price of oil has intensified again (Kilian, 2016). Our time-varying and more nuanced results are in contrast with time-invariant studies, which have argued that oil supply shocks have played a minor role in explaining oil price fluctuations, since only in the 1990's and 2000's was supply less important (e.g., Kilian, 2009; and Abhyankar et al., 2013).

Secondly, we find that the real price of oil has responded positively to aggregate demand shocks over the entire sample period - see middle panels of Figures 6-8. Our estimated results are in line with previous studies showing that an expansion in the global economy increases demand for industrial commodities and drives up oil prices (e.g., Kilian, 2008; Frankel, 2014). We also find that the effect of real economic activity on oil prices is time-varying. In this regard, we confirm the findings by Kilian (2009) and Abhyankar et al. (2013) indicating that the relationship between aggregate demand and the real price of oil was weaker during the 1980's and the 1990's whereas it has intensified in the mid-2000's in correspondence with the unexpected increase in demand from many emerging economies. The peak impact of demand was around the global financial crisis.

4.3.2 Response of Oil Price to Business Leaders' Expectations

The bottom panel of Figure 6 shows that positive shocks to business leaders' expectations have a substantial and positive impact upon oil prices. Importantly, we note that the impact of business leaders' expectations upon oil prices is very time-dependent. In general, business leaders' expectations have a large influence on physical oil demand (Angeletos et al., 2015). This may be explained by the fact that business managers have extensive access to information and possibly a better understanding of economic news and analyses which also informs their investment, production and pricing decisions (e.g., Bachmann and Sims, 2012; Delis et al., 2014; and Caglayan and Xu, 2016).

However, in the presence of informational frictions, firms' managers are not able to influence the real oil price through the oil supply channel. In particular, they are not able to differentiate between oil demand and supply shocks (Sockin and Xiong, 2015). For example, in the case of an oil supply shock, they partially attribute such a shock to demand. In such a situation, the information content of business leaders is relatively low and their influence on the oil price is limited.

The time-varying response of oil prices to business leaders' expectations can be better understood focusing upon the main oil episodes during the period 1985-2016. From the top panel of Figure 6, we note that since the mid-1980's until the beginning of the 1990's oil supply shocks have played an important role in oil price changes. In this regard, the first significant episode of oil price increase in our sample is at the beginning of the 1990's corresponding to the Iraq-Kuwait war. As we have explained above, business leaders' expectations have a negligible influence on the oil price through the oil supply channel. Therefore, from the bottom panel of Figure 6 we observe that during this period the oil price response to a BCI shock is not substantial.

From the middle panel of Figure 6, we note that in the period 2002-2008 an important source of oil price changes has been oil demand. In particular, the increase in the oil price during this period coincided with the sustained global oil demand pressure mainly from emerging countries. Global growth in oil demand during this period was exceptional.[15] As we have explained above, business leaders' expectations strongly affect oil demand. Therefore, from the bottom panel of Figure 6, we note that the response of the oil price to BCI shocks is important over this period.

[15] See, for example, Hamilton (2009).

Cheng and Xiong (2014) observed that, in the period 2009-2014 heterogenous expectations among business leaders led these agents to engage in speculative trading against each other, which, in turn, induced the oil price to drift away from its fundamental value. In this regard, Lorusso and Pieroni (2018) have argued that the increase in the oil price between 2009-2014 was mainly associated with a strong precautionary demand for oil. In particular, the social and political instability in the Middle East and North African regions raised worries of supply disruptions and possible oil shortage. Therefore, from the bottom panel of Figure 6, we note that in the period following the financial crisis BCI shocks largely affect oil price movements.

Finally, from 2014 onwards the dramatic fall in the oil price has been related to the increase in oil production, namely, the US tight oil (Baumeister and Kilian, 2016). In particular, the US re-emerged as a main oil producer extracting oil through the hydraulic fracturing, the so-called shale oil revolution. As we can see from the bottom panel of Figure 6, during this period BCI shocks have a less important impact on the oil price.

4.3.3 Response of Oil Price to Consumers' Expectations and Markets' Expectations

Our estimated results indicate a weak link between consumers' confidence and oil prices. The negative sign of the relationship between consumer expectations and oil prices is a puzzle. However, from the bottom panel of Figure 7 we observe that, since the beginning of the financial crisis, although there is some evidence of time variation in the response of the real price of oil, the posterior intervals are so wide to leave open the possibility that the consumers' confidence shocks is not important.

From the bottom panel of Figure 8, we note that the response of the oil price to increases in market expectations is initially negative whereas, from 2000's onwards it becomes positive. However, the posterior intervals are very large suggesting the responses remained unchanged. This result may be explained by the nature of composite leading indicators combining the expectations of business leaders and consumers. As we have seen in Figures 6 and 7, business leaders and consumers shocks have opposite effects on oil prices. Therefore, aggregate expectations have an ambiguous effect on the real oil price. In conclusion, our empirical findings highlight the importance for allowing for heterogeneous expectations across economic agents (Baumeister and Kilian, 2016). In this regard, our results are consistent with the arguments from Morris and Shin (2002) and Sockin and Xiong (2015).

4.4 Robustness Checks

We now report some robustness checks for our TVP-VAR model, and the results are in Appendix B. We begin our robustness analysis by considering the potential role of refineries' expectations in our model. In particular, oil refineries could have their own expectations about the future, which could be different in principle from business leaders and consumers. Unlike for businesses', consumers' or markets' expectations, there are not specific surveys that have been produced to capture refiners' confidence. Given crude oil is storable, the price of oil and refined oil products are highly correlated. Oil refineries have the incentive to adjust their demand and holding of inventories to minimize their input costs. For example, if refineries are expecting an increased uncertainty about the oil market demand or supply conditions they can increase their demand for oil with the intention to store for future use. As a consequence, these activities can raise the futures price of oil, which in turn would drive up the spot price as less of the oil is made available for current consumption (e.g., Kilian and Murphy, 2014). On the other hand, refineries may reduce their inventories by predicting a global recession, and/or anticipate higher level of future oil production.

In order to proxy the impact of refineries' expectations on oil prices, we collected data for OECD inventories from the International Energy Agency (IEA) for the period of 1974:Q4 to 2016:Q1. We obtained the series of refineries' inventories as the difference of total crude oil stocks and crude oil stocks held by governments.[16] According to Knit-

[16]Note that IEA only provide total crude oil stocks at annual frequency for the period 1974 to 1983.

tel and Pindyck (2016) such series can be interpreted as a forward-looking time series because fluctuations in inventories can be considered as a proxy of variations in agents' expectations. [17] Therefore, we re-estimated our TVP-VAR model with refineries' expectations instead of our other measures of expectations. As we can observe from Figure B1, an increase in refineries' expectations does not substantially affect the real oil price since the zero axis is within the error bands. Accordingly, our findings suggest that refiners' expectations have a negligible effect on oil prices.

As a second robustness check, we have investigated the robustness of our results to potential omitted variable bias by considering our three expectations measures simultaneously. Firstly, we used the principal component analysis to extract a common factor from BCI, CCI and CLI. Then, we re-estimated the TVP-VAR model replacing the original expectations indexes with the new created series. Figure B2 shows the IRFs of the oil price in the presence of shocks to aggregate expectations of business leaders, consumers and markets. We note that the response is not important implying that changes in aggregate expectations do not affect the real oil price. We also included all expectations measures and other fundamentals in a single TVP-VAR model - see Figure B3. However, consistent with Kilian (2013) the results were difficult to interpret and may have been susceptible to problems with over-fitting. As we can notice from the estimated results, the response of the real price of oil is weak not only in the case of expectations' shocks but also for oil market fundamentals shocks.[18]

Our third robustness check focuses on the series of the oil price. In particular, many previous studies analysing the determinants of oil price fluctuations have considered the impact of US refiner acquisition cost of imported crude oil (see, for example, Barsky and

We disaggregated these data into quarterly frequency using the Denton (1971) approach. Moreover, for the same period, data for crude oil stocks held by government are missing. In order to obtain the series of refineries inventories we used the growth rates of quarterly total crude oil stocks. Following this procedure, we implicitly assumed that the share of government stocks for to period 1974:Q3-1983:Q4 has been stable and equal to that of 1984:Q1. Our assumption is based on the fact that this share has been almost constant (around 30%) for the period 1984-1987.

[17] We would like to thank one of the anonymous referees suggesting to consider the role of inventories.

[18] As suggested by a helpful Reviewer we were not able to entirely rule out omitted variable bias from our results, although this is ameliorated by the degree of correlation between the expectation variables and also small scale VARs are widely used to avoid over-fitting in this literature.

Kilian, 2004; Kilian, 2009; Kilian and Murphy, 2012). Therefore, we re-estimated our models by replacing the series of the Europe Brent spot price with this series. Table B1 suggests that the responses of oil prices to oil supply, aggregate demand and expectations shocks are in line with those reported in Figures 6-8.

The fourth robustness check provides evidence that our assumptions about the identification order adopted in our impulse response analysis do not influence the main empirical findings. Table B2 shows that the directions of the responses to the structural shocks are qualitatively similar when we placed the economic agents' expectations first in equation (2). Finally, we replace the economic agents' expectations emanated from all OECD countries to the US market only. The estimated impulse response functions of oil prices to oil market fundamentals and expectations shocks are shown in Table B3. Again, this robustness check does not qualitatively change our main findings.

5 Conclusion

Modelling oil price movements is important to many decision makers in macroeconomic policy, capital investment/production decisions, consumption, risk and portfolio management. The oil price is considered as an important barometer for the global economy (Sockin and Xiong, 2015; Ravazzolo and Rothman, 2016).

Our paper extends the topical literature on identifying the determinants of oil prices, by emphasising the role of economic agents' expectations. Our investigation focuses upon expectations from three sources: business leaders, consumers and markets. Oil price may not fully reflect fundamentals since agents can have severe informational frictions. In this context expectations impact oil prices, although the source of these expectations matters. Our empirical strategy is based on a TVP-VAR model with stochastic volatility to flexibly delineate the impact of fundamentals and economic agents' expectations.

Our estimated results show that both traditional fundamentals and heterogeneous economic agents' affect oil prices over time. We find that the source of economic expectations matters. In particular, innovations to business leaders' expectations greatly affect oil price movements. We provide evidence that increases in business leaders' expectations have a large and positive impact upon the real price of oil. This effect increases during periods of high oil demand. Our findings also show that consumers' expectations only explain a small proportion of overall oil price variability.

In sum, our empirical evidence is consistent with the idea that there is non-constant relationship between traditional oil market fundamentals and heterogenous economic agents' expectations. Therefore, regulators should consider how their policies (e.g., capital and asset allocation, taxes, and environmental policies) shall be perceived by firms' mangers and households. Moreover, informational frictions and expectations may be important for other commodity prices, such as metals and agricultural price. We shall leave these topics for future work.

Acknowledgement

We are grateful to Dr. Paola Zerilli and Prof. Rita D'Ecclesia for their specific comments as well as those of participants in the "58^{th} Euro Working Group for Commodities and Financial Modelling", University of York, December 2016. We would like to thank the two anonymous referees for kindly agreeing to provide a review of our manuscript, for their careful reading of our work and their helpful comments. We appreciate the feedback on this article from António Carvalho, Jan Ditzen, Gary Koop, Antonio Parlavecchio, Francesco Ravazzolo and Mark Schaffer. We are grateful for the financial support provided by the Carnegie Trust for the Universities of Scotland. The standard disclaimer applies.

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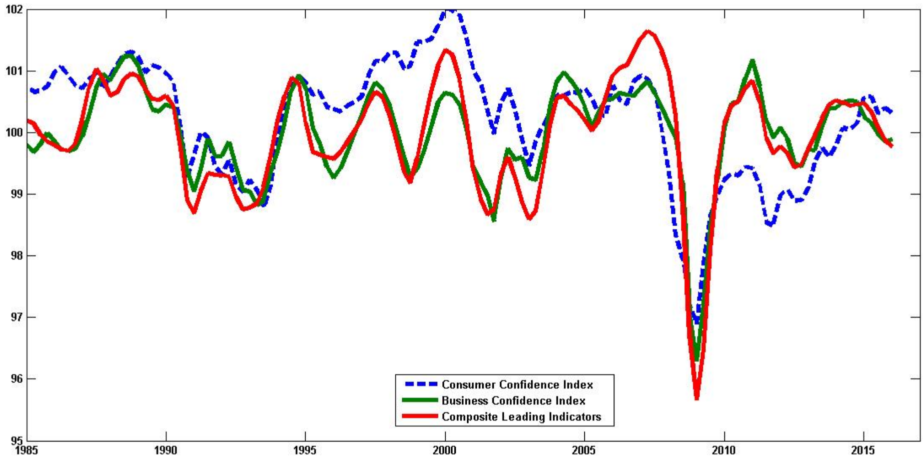
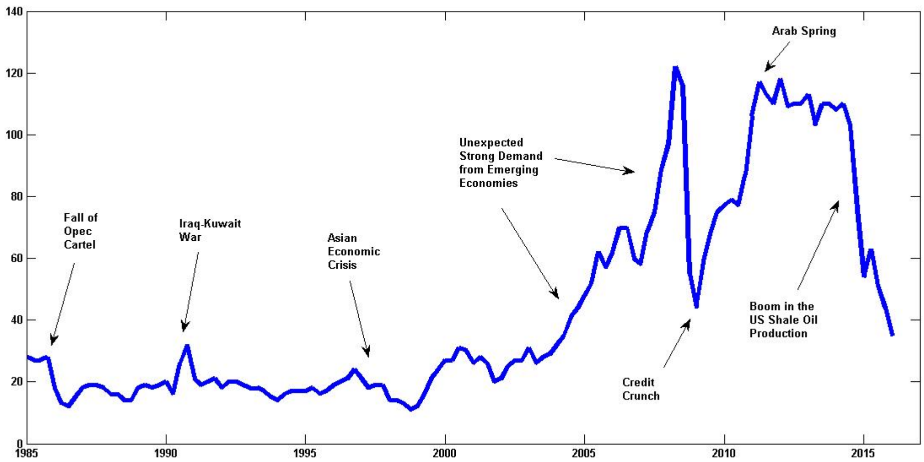
Figure 1: Time Series Proxies of Economic Agents' Expectations



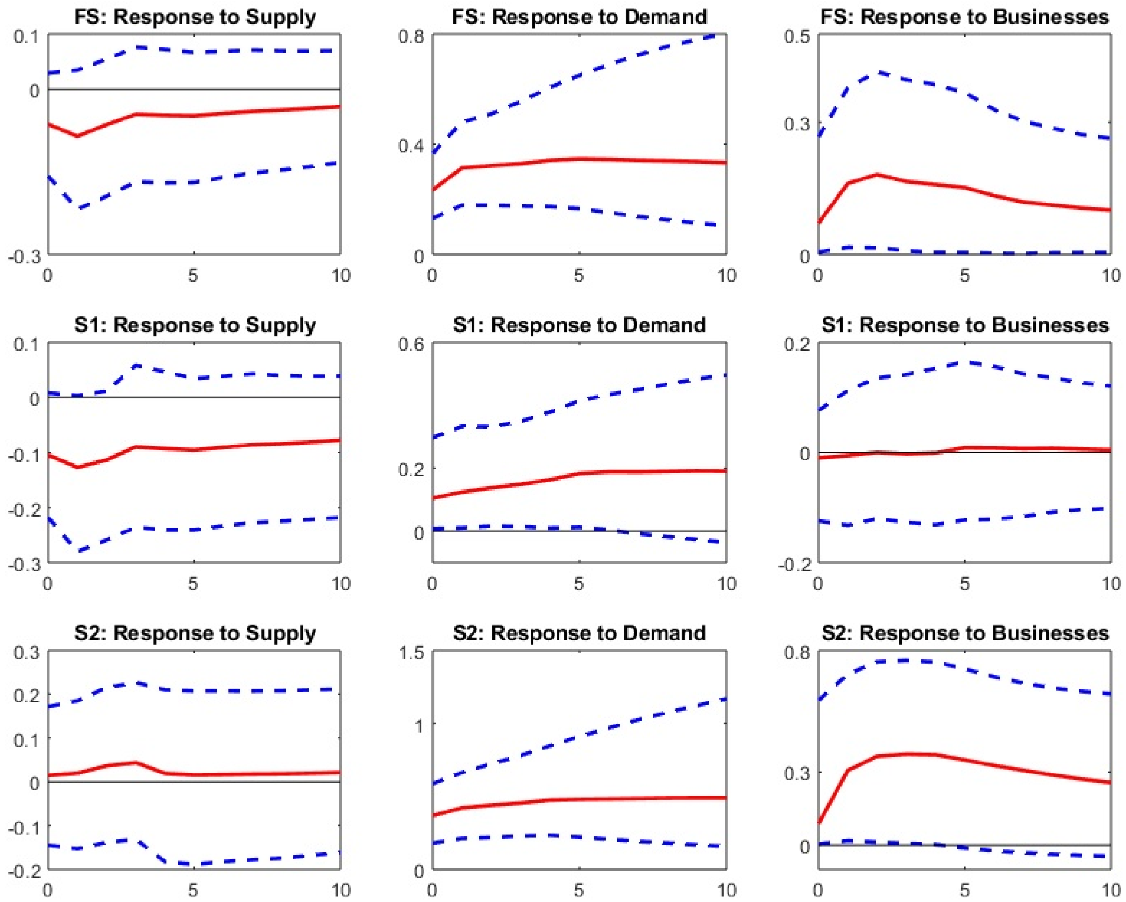
Notes: This figure contains time series data based upon business leaders' expectations as proxied by OECD Business Confidence Index (BCI). Also included are consumers' expectations as proxied by Consumer Confidence Index (CCI). Finally, we proxy market analysts' expectations using Composite Leading Indicators (CLI).
Source: OECD Monthly Main Economic Indicators Database.

Figure 2: Europe Brent Spot Crude Price FOB



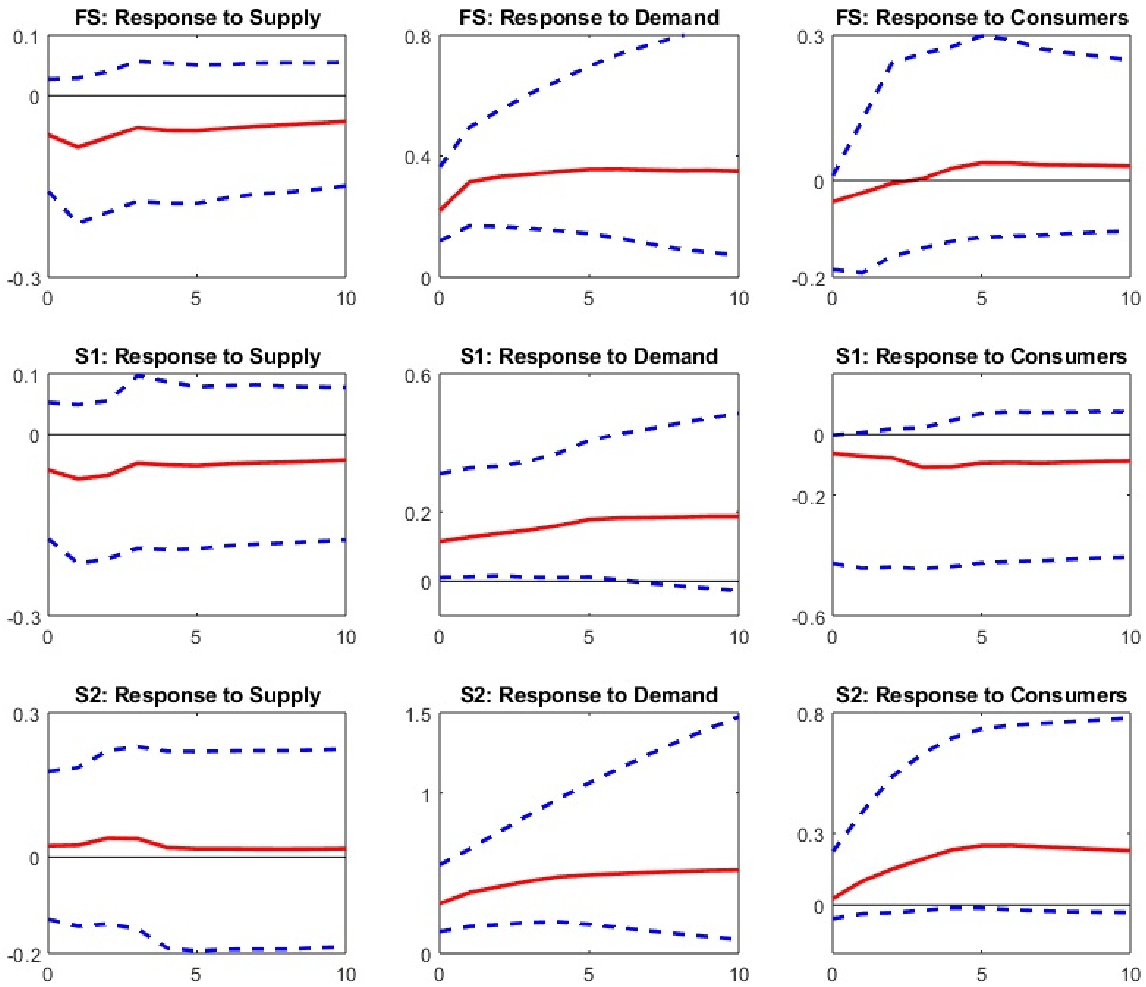
Notes: Europe Brent Spot Price FOB (US dollars per barrel) and major oil price episodes.
Source: Datastream database.

Figure 3: BVAR Impulse Responses of Real Price of Oil under Business Leaders' Expectations



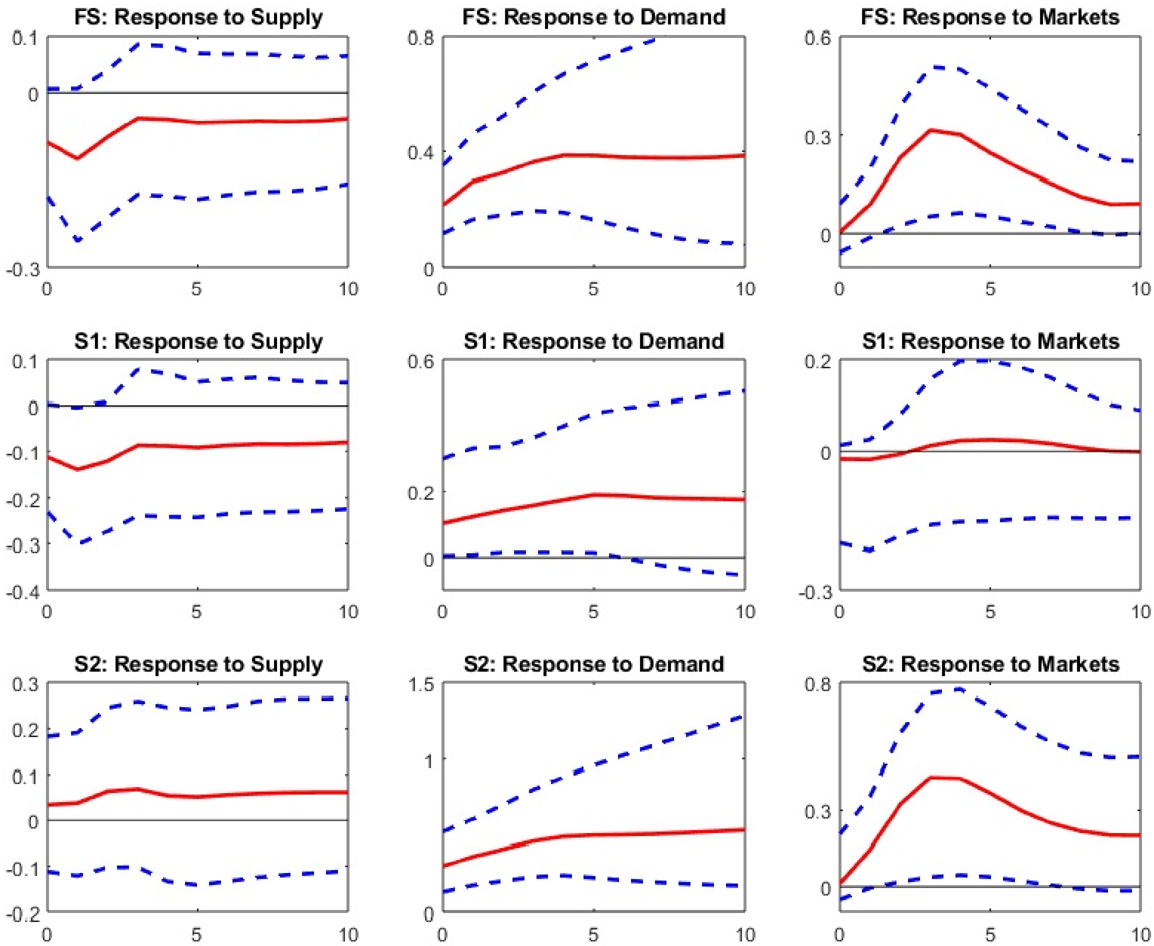
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and Business Confidence Indicator (BCI). The first row reports the IRFs for the full sample period (1974:Q4-2016:Q1) whereas, the second and third rows report the IRFs for two sub-samples 1974:Q4-1998:Q4 (S1) and 1999:Q1-2016:Q1 (S2), respectively.

Figure 4: BVAR Impulse Responses of the Real Price of Oil under Consumers' Expectations



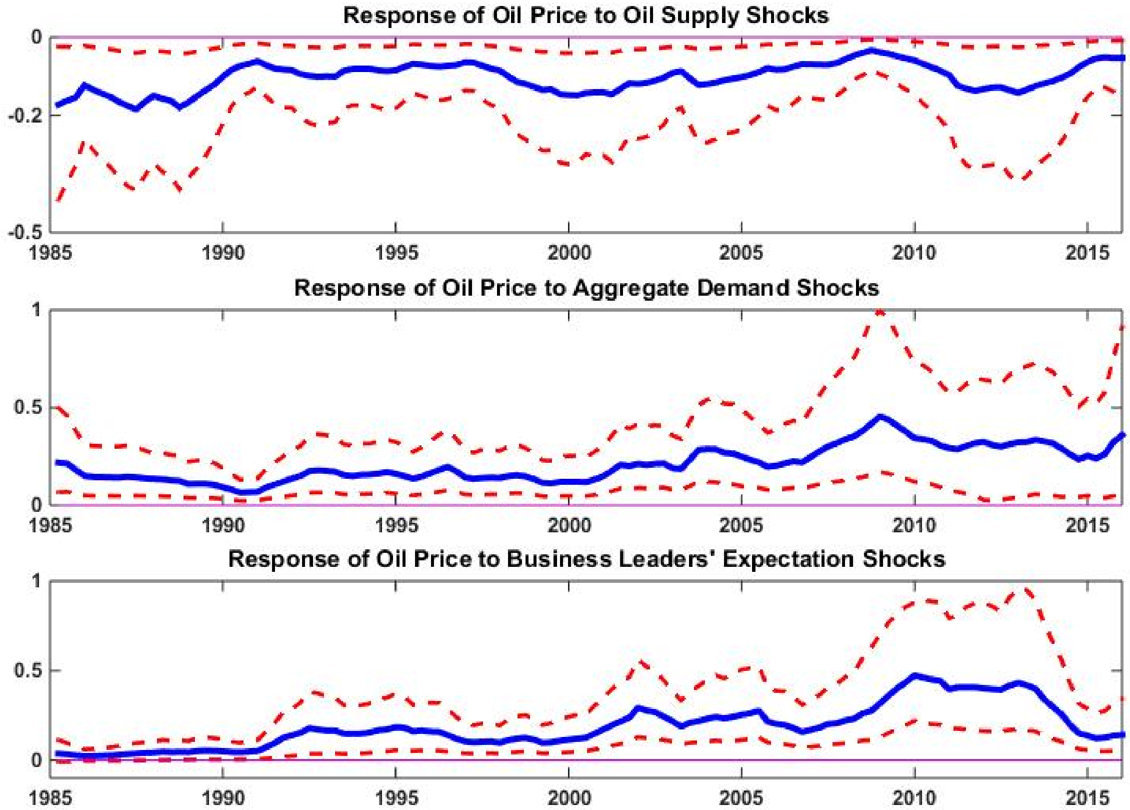
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the $16th$ and $84th$ percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and Consumer Confidence Indicator (CCI). The first row reports the IRFs for the full sample period (1974:Q4-2016:Q1) whereas, the second and third rows report the IRFs for two sub-samples 1974:Q4-1998:Q4 (S1) and 1999:Q1-2016:Q1 (S2), respectively.

Figure 5: BVAR Impulse Responses of the Real Price of Oil under Markets' Expectations



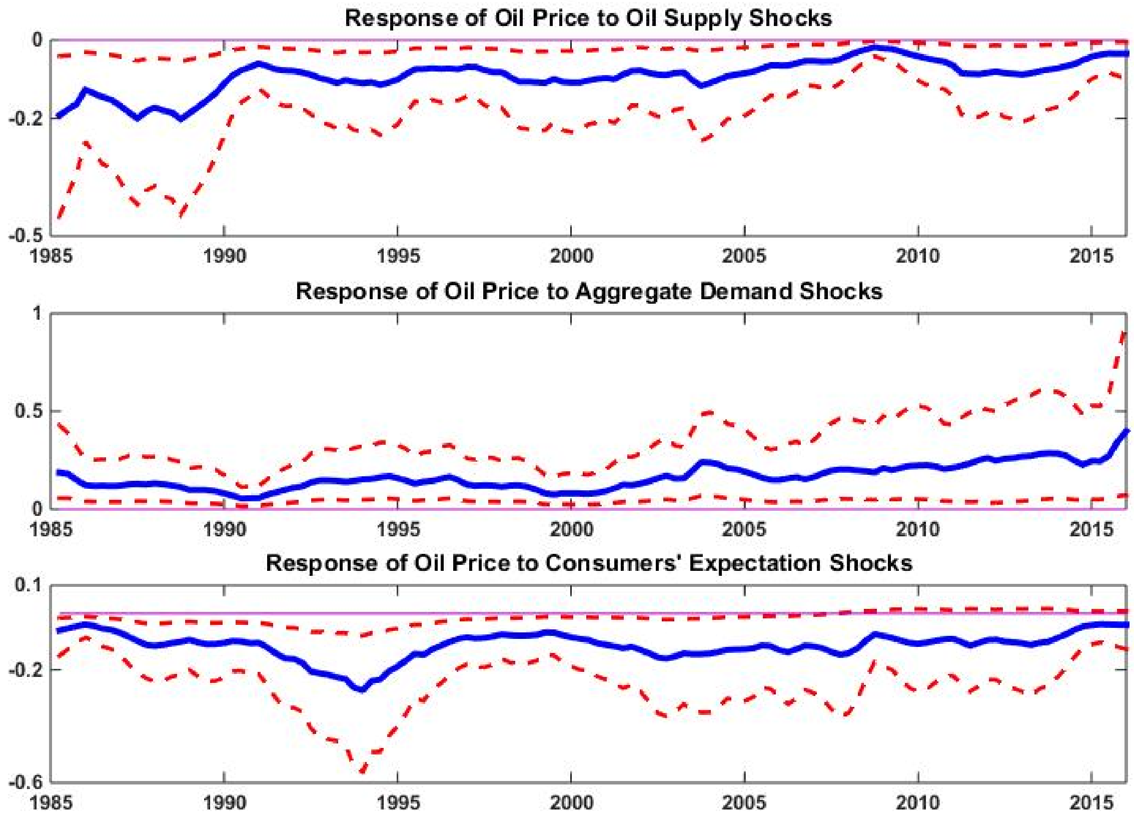
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and Composite Leading Indicator (CLI). The first row reports the IRFs for the full sample period (1974:Q4-2016:Q1) whereas, the second and third rows report the IRFs for two sub-samples 1974:Q4-1998:Q4 (S1) and 1999:Q1-2016:Q1 (S2), respectively.

Figure 6: TVP-VAR Impulse Responses of Real Price of Oil under Business Leaders' Expectations



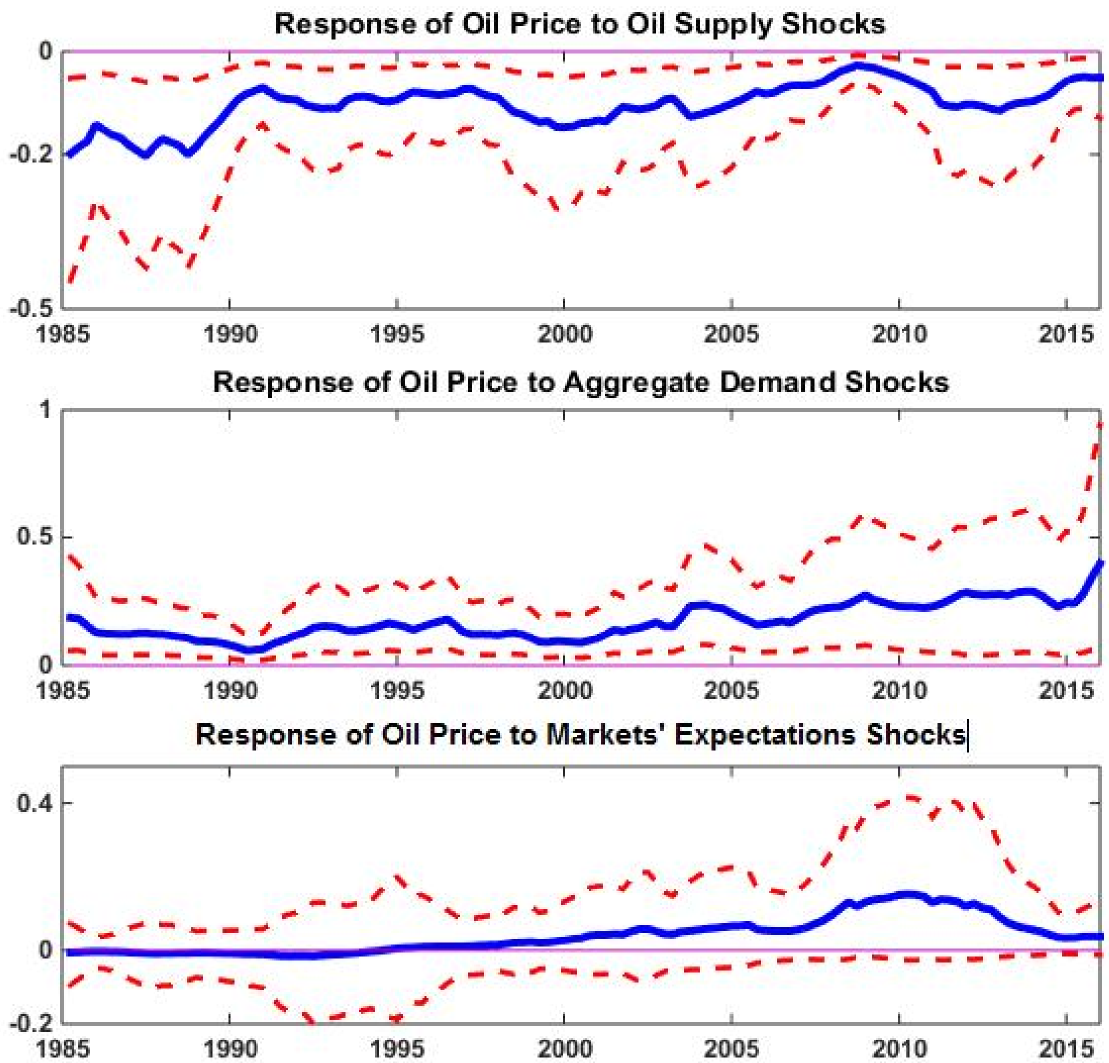
Notes: Each panel measures how a unit impulse of several shocks impacts the oil price over the full sample period. In each panel solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and Business Confidence Indicator (BCI). The estimates are based on the TVP-VAR model with Stochastic Volatility.

Figure 7: TVP-VAR Impulse Responses of Real Price of Oil under Consumers' Expectations



Notes: Each panel measures how a unit impulse of several shocks impacts the oil price over the full sample period. In each panel solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and Consumer Confidence Indicator (CCI). The estimates are based on the TVP-VAR model with Stochastic Volatility.

Figure 8: TVP-VAR Impulse Responses of Real Price of Oil under Markets' Expectations



Notes: Each panel measures how a unit impulse of several shocks impacts the oil price over the full sample period. In each panel solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and Composite Leading Indicator (CLI). The estimates are based on the TVP-VAR model with Stochastic Volatility.

Table 1: Data Sources and Definitions

Variable	Data Series	Definition	Sources of Data
Percentage change in global oil production	Global Oil Production	World crude oil production in millions per barrels pumped per day (averaged by quarter).	Energy Information Administration, Monthly Energy Review
Global real economic activity	Single-voyage freight rates	See Kilian (2009) for detailed information on how to construct this series.	Lutz Kilians homepage: http://www-personal.umich.edu/ lkil-ian/reaupdate.txt.
Economic Agents' Expectations	Business Confidence Indicator (BCI)	BCI is a composite indicator that summarizes managers' assessments and expectations of the general economic situation.	OECD Monthly Main Economic Indicators database.
	Consumer Confidence Indicator (CCI)	CCI includes indicators on consumer confidence, expected economic situation and price expectations.	
	Composite Leading Indicator (CLI)	CLI is an aggregate time series displaying a reasonably consistent leading relationship with the reference series (e.g., industrial production up to March 2012 and GDP afterwards) for the macroeconomic cycle in a country. CLI is designed to provide early signals of turning points between expansions and slowdowns of economic activity.	
Real oil Price	Europe Brent spot price FOB	The original series is aggregated in quarterly terms and deflated using the US CPI.	DataStream

Table 2: Variance Decomposition of the Real Price of Oil

Panel (*i*): Model Including Business Leaders' Expectations				
Horizon	**Supply Shock**	**Demand Shock**	**BCI Shock**	**Residual Shock**
1	3.72%	13.05%	7.15%	76.09%
4	6.62%	23.29%	16.15%	53.94%
12	5.07%	42.62%	11.18%	41.12%
∞	4.24%	51.85%	9.36%	34.55%
Panel (*ii*): Model Including Consumers' Expectations				
Horizon	**Supply Shock**	**Demand Shock**	**CCI Shock**	**Residual Shock**
1	5.08%	11.67%	1.13%	82.11%
4	9.36%	24.76%	1.88%	63.99%
12	7.82%	41.84%	3.18%	47.17%
∞	7.24%	46.92%	3.54%	42.30%
Panel (*iii*): Model Including Markets' Expectations				
Horizon	**Supply Shock**	**Demand Shock**	**CLI Shock**	**Residual Shock**
1	4.58%	11.81%	0.01%	83.61%
4	9.20%	23.77%	7.70%	59.32%
12	8.16%	40.17%	6.43%	45.23%
∞	7.20%	48.21%	5.80%	38.79%
Panel (*iv*): Model without Expectations				
Horizon	**Supply Shock**	**Demand Shock**	**Residual Shock**	
1	2.72%	12.91%	84.38%	
4	6.37%	21.36%	72.27%	
12	4.77%	40.30%	54.93%	
∞	4.13%	48.23%	47.64%	

Notes: The variance decomposition of the real oil price is based on the estimates of the BVAR model for the full sample. The table presents the percentage contribution of each shock to the overall variability of the real oil price for one quarter, four quarters, twelve quarters and infinity.

Appendix A: Constant BVAR and TVP-BVAR Models

This appendix shows the full derivation of both constant parameter Bayesian VAR and time-varying parameter Bayesian VAR with stochastic volatility.

In the constant parameter Bayesian VAR we employ the reduced-form representation of equation (1) in the main text by multiplying both sides by A_0^{-1}, resulting in:

$$Y_t = \Sigma_{i=1}^{p} B_i Y_{t-1} + A_0^{-1} u_t \tag{A1}$$

where $B_i = A_0^{-1}\Gamma_i$ for $i = 1, ..., p$ and u_t is i.i.d. $N(0, \Sigma)$. We can stack all the VAR coefficients (B_i) into a $K^2p \times 1$ vector to form B and define $X_t = I_k \otimes (Y_{t-1}^{'}, ..., Y_{t-p}^{'})$, where $\otimes$ denotes the Kronecker product. We rewrite equation (A1) as:

$$Y_t = X_t B + A_0^{-1} u_t \tag{A2}$$

Note that the reduced-form residuals $\varepsilon_t = A_0^{-1} u_t$ are correlated between each equation. In order to orthogonalize the shocks, we impose a recursive structure on the contemporaneous terms and assuming that A_0^{-1} is lower-triangular:

$$A_0^{-1} = \begin{pmatrix} 1 & 0 & \dots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \dots & a_{k1,k-1} & 1 \end{pmatrix} \tag{A3}$$

The ordering of the variables is as follows: $Y_t = [\Delta prod_t, rea_t, \Delta exp_t, rpo_t]$. Our restrictions on A_0^{-1} are based on the following assumptions and economic intuitions. Our first assumption is that, instantaneously, global oil supply does not respond to short-run demand shocks in the crude oil market. This is plausible since, in the short-run, changes in oil production are costly, largely irreversible and can be delayed. Therefore, oil producers adopt a wait and see approach, and base their production plans on expectations of medium-term demand (see e.g., Hamilton, 2009; Kilian and Murphy, 2012). The second assumption we make is that increases in the real price of oil, say driven by agents' expectations or oil-market specific demand, do not immediately impact global economic activity. This assumption relies on the absence of evidence of instantaneous feedback from changes in the real oil price and agents' expectations to the dry cargo ocean freight rates: the latter is Lutz Kilian's measure of global real activity (see for example, Kilian and Murphy, 2014; Gao et al., 2017). Our third assumption is that changes to economic expectations respond to supply and demand shocks without a delay. In particular, Bernanke et al. (2005), and Stock and Watson (2005) have classified agents' expectations as a fast-moving variable, responding contemporaneously to slow-moving variables, such as oil production and global real economic activity. Finally, shocks to the real oil price that are not explained by oil supply shocks, aggregate demand shocks or expectations' shocks by construction reflect the residual shocks not otherwise accounted for.

As described in the main text the constant parameter VAR model is estimated with Bayesian techniques. We adopt the independent Normal-Wishart prior:

$$B \sim N(\underline{B}, \underline{V_B})$$
$$\Sigma^{-1} \sim W(\underline{S}^{-1}, \underline{v})$$

where $\underline{B} = 0$, $\underline{V_B} = 10I_4$, $\underline{S} = I_4$, and $\underline{v} = 5$ are as in Koop and Korobilis (2010). The conditional posterior distributions $p(B \mid Y, \Sigma^{-1})$ and $p(\Sigma^{-1} \mid Y, B)$ are computed by the MCMC method. Following Primiceri (2005), we use a training sample prior to obtain the initial Σ^{-1}.

In the time-varying parameter Bayesian VAR with stochastic volatility equation (A2) becomes:

$$Y_t = X_t B_t + A_t^{-1} u_t \tag{A4}$$

where B_t and A_t^{-1} are time-varying and u_t is i.i.d. $N(0, \Sigma_t)$. We follow Primiceri (2005) and assume that a_t is the vector of non-zero and non-one elements of the matrix A_t (stacked by rows) and σ_t is the vector of the diagonal elements of Σ_t. The parameters in (A4) follow a driftless random walk process, thus allowing both temporary and permanent shift in the parameters. Assuming that $h_t = \log \sigma_t$, we can write:

$$B_t = B_{t-1} + v_t \tag{A5}$$

$$a_t = a_{t-1} + \zeta_t \tag{A6}$$

$$h_t = h_{t-1} + \eta_t \tag{A7}$$

All the innovations in the model are assumed to be jointly normally distributed with the following assumptions on the variance-covariance matrix (V):

$$\begin{pmatrix} u_t \\ v_t \\ \zeta_t \\ \eta_t \end{pmatrix} \sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{pmatrix} \right), t = 1, ..., T$$

where I is an n-dimensional identity matrix, Q, S and W are positive definite matrices. The shocks to the innovations of the time-varying parameters are assumed uncorrelated among the parameters B_t, a_t and h_t. We further assume for simplicity that Q, S and W are all diagonal matrices. Following Primiceri (2005), we adopt the additional assumption of S being block diagonal, with blocks corresponding to parameters belonging to separate equations. The coefficients of the contemporaneous relations among variables are assumed to evolve independently in each equation. Our dynamic specification permits the parameters to vary and the shock log variance follows a random walk process to capture possible gradual or sudden structural changes, as discussed by Primiceri (2005). As before, we employ a training sample prior and the prior distributions are set as follows:

$$B_0 \sim N(B_{OLS}, 4 \cdot V(B_{OLS}))$$
$$a_0 \sim N(a_{OLS}, 4 \cdot V(a_{OLS}))$$
$$h_0 \sim N(h_{OLS}, 4 \cdot I_k)$$

where B_{OLS}, A_{OLS}, and h_{OLS} denote the OLS point estimates and $V(\cdot)$ denotes the variance. We also need to set the hyper-parameters Q, S, and W and we postulate the following inverse-Wishart prior distributions:

$$Q \sim IW(k_Q^2 \cdot 40 \cdot V(B_{OLS}), 40)$$
$$W \sim IW(k_S^2, 2)$$
$$S_1 \sim IW(k_T^2 \cdot 2 \cdot V(A_{2,OLS}), 2)$$
$$S_2 \sim IW(k_T^2 \cdot 3 \cdot V(A_{3,OLS}), 3)$$
$$S_3 \sim IW(k_T^2 \cdot 4 \cdot V(A_{4,OLS}), 4)$$

where $k_B = 0.01$, $k_\alpha = 0.1$, and $k_h = 1$. Moreover, S_1, S_2, and S_3 denote the three blocks of S, respectively. $A_{2,OLS}$, $A_{3,OLS}$ and $A_{4,OLS}$ are the three corresponding blocks of A_{OLS}.[19].

We follow the MCMC procedures proposed by Primiceri (2005) and the estimation process are as follows:

1. Initialize A_t, Σ_t, h_t and V;
2. Conditional on Y_t, B_t, Σ_t and V, draw VAR coefficients B_t;
3. Conditional on Y_t, B_t, Σ_t and V, draw contemporaneous coefficients A_t;
4. Conditional on Y_t, A_t, B_t, h_t and V, draw covariance matrix parameters for residuals Σ_t;

[19] S_1 includes information on a_{21}; S_2 contains information on a_{21}, a_{31}, and a_{32}; S_3 embraces information on a_{21}, a_{31}, a_{32}, a_{41}, a_{42} and a_{43}

5. Conditional on Y_t, A_t, Σ_t and V, draw volatility states h_t;

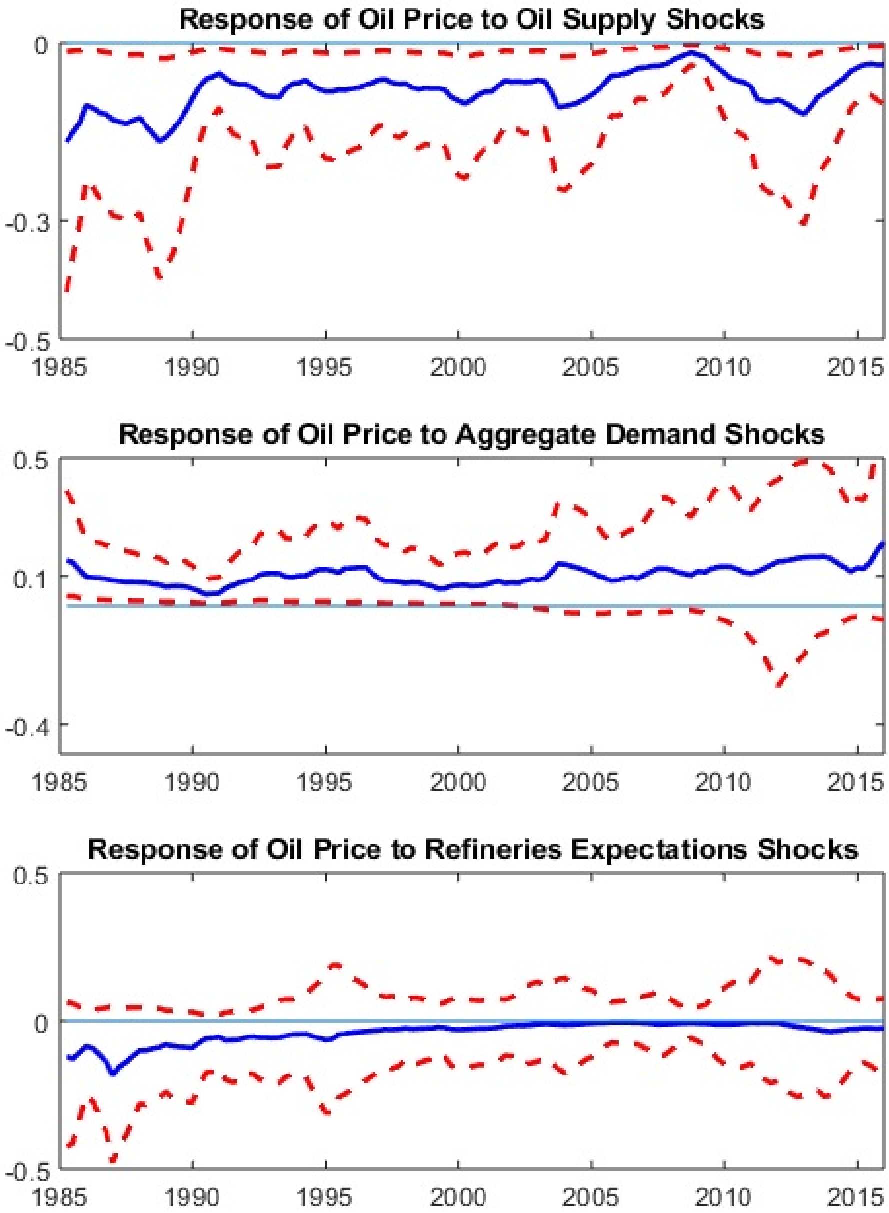
6. Draw hyperparameters V, which is obtained by drawing Σ_B, Σ_a, and Σ_h. The hyperparameters Σ_B, Σ_a, and Σ_h are square blocks, and each block has an invers-Wishart distribution which is independent from other blocks;

7. Return to #2.

The details of this algorithm are shown in the Appendix of Primiceri (2005).

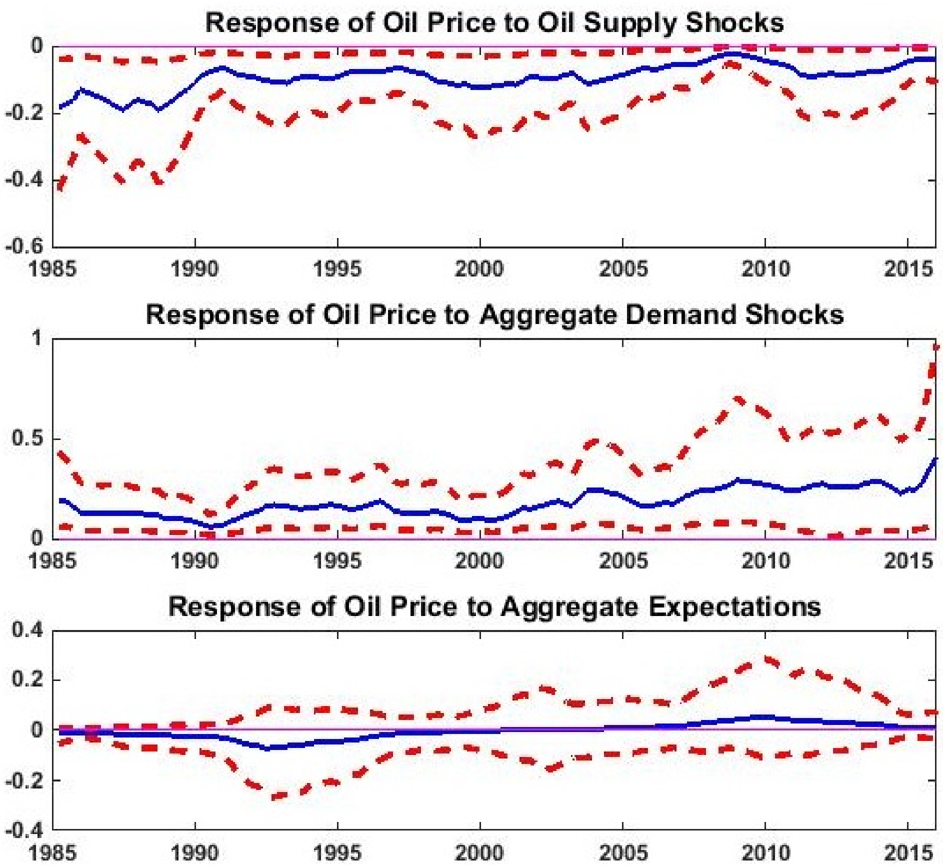
Appendix B: Robustness Checks

Figure B1: TVP-VAR Impulse Responses of Real Price of Oil under Refineries' Expectations



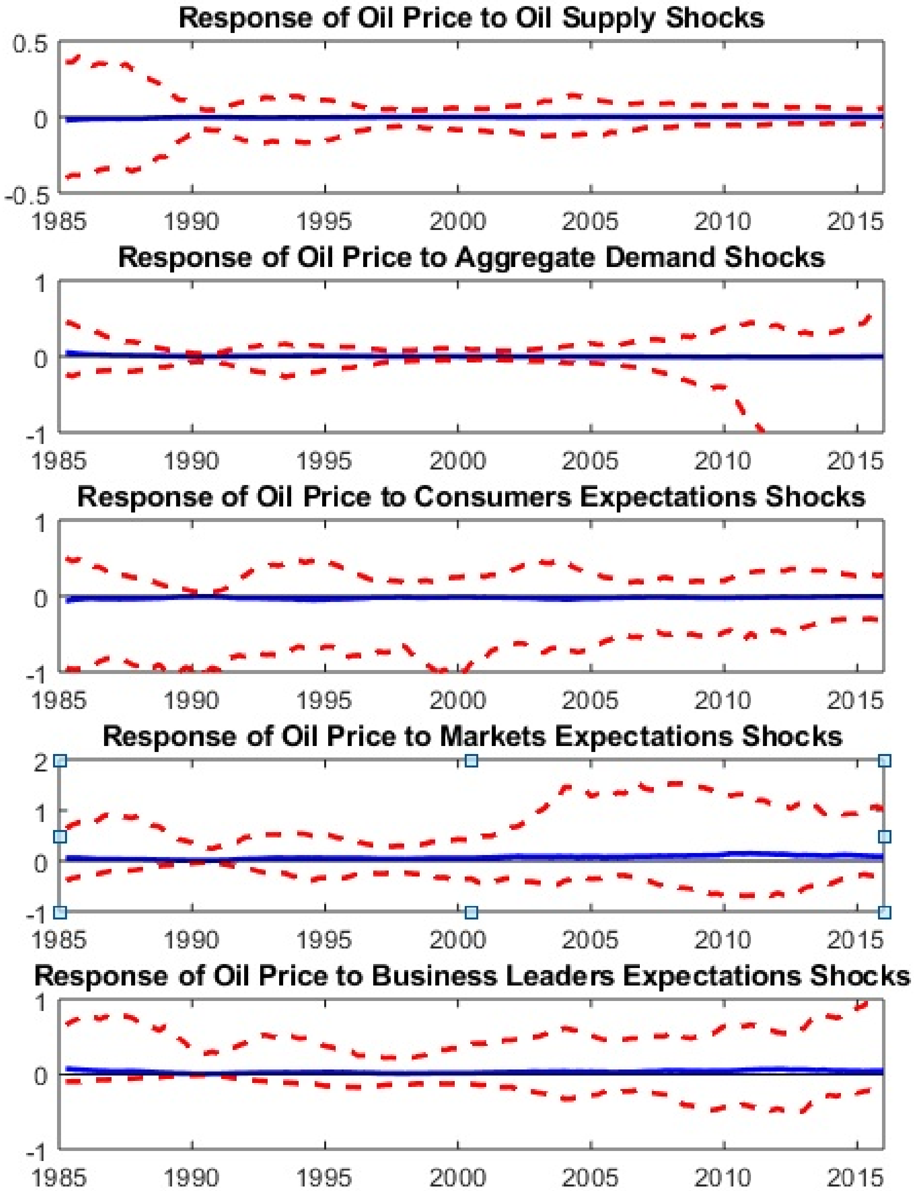
Notes: Each panel measures how a unit impulse of several shocks impacts the oil price over the full sample period. In each panel solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and refineries' expectations. The estimates are based on the TVP-VAR model with Stochastic Volatility.

Figure B2: TVP-VAR Impulse Responses of Real Price of Oil under Aggregate Expectations



Notes: Each panel measures how a unit impulse of several shocks impacts the oil price over the full sample period. In each panel solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and aggregate expectations. The estimates are based on the TVP-VAR model with Stochastic Volatility.

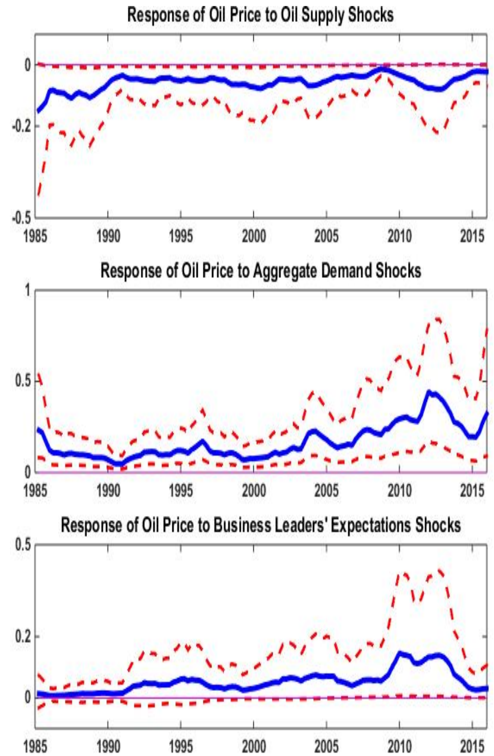
Figure B3: Impulse Responses of Real Oil Price Obtained from Six Variable TVP-VAR

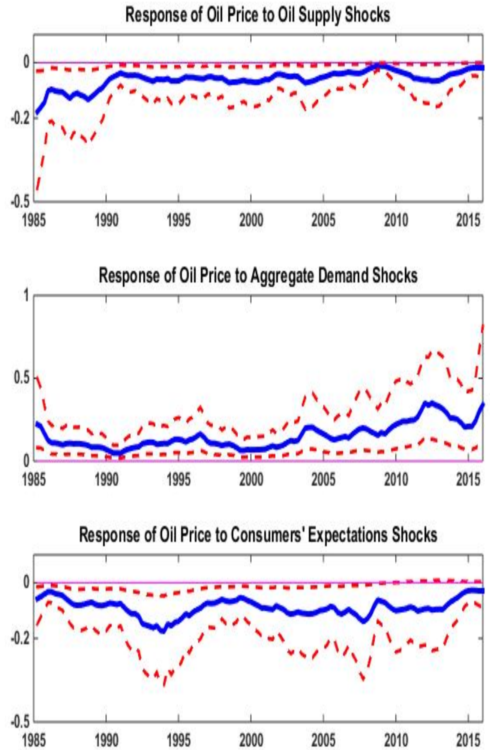


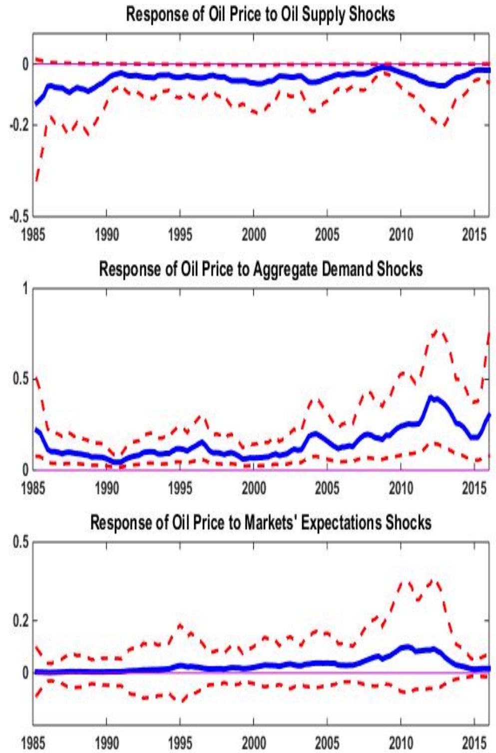
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider five different shocks to oil prices: oil supply, aggregate demand, Consumer Confidence Indicator (CCI), Composite Leading Indicator (CLI) and Business Confidence Indicator (BCI). The estimates are based on the TVP-VAR model with Stochastic Volatility.

Table B1: Replacing Brent Crude with US Refiner Acquisition Cost of Imported Crude Oil

Panel A: Responses of oil prices to fundamentals and business leaders' expectations shocks	**Panel B:** Responses of oil prices to fundamentals and consumers' expectations shocks	**Panel C:** Responses of oil prices to fundamentals and markets' expectation shocks



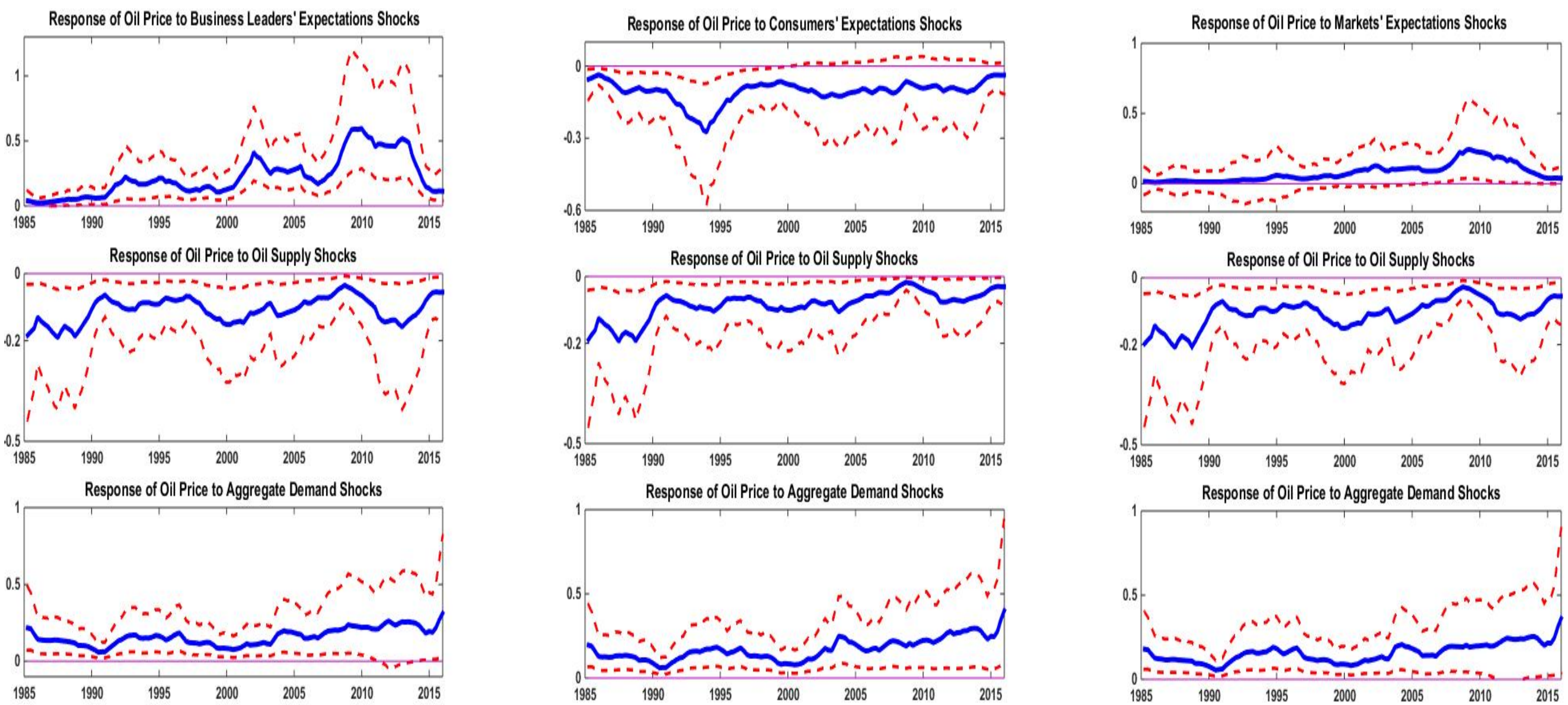




Notes: Each figure measures how a unit impulse of several shocks impacts the oil price over the full sample period. In each panel solid lines represent the median responses whereas dashed lines indicate the 16*th* and 84*th* percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and expectations. The estimates are based on the TVP-VAR model with Stochastic Volatility.

Table B2: Different Ordering of the Variables

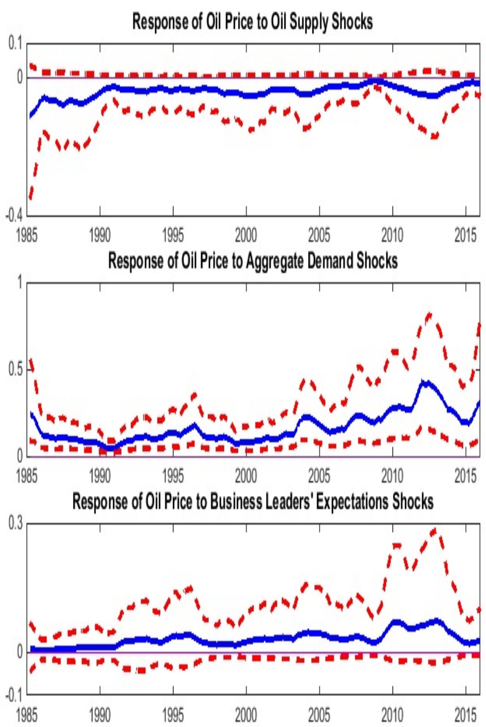
Panel A: Responses of oil prices to fundamentals and business leaders' expectations shocks	**Panel B:** Responses of oil prices to fundamentals and consumers' expectations shocks	**Panel C:** Responses of oil prices to fundamentals and markets' expectation shocks

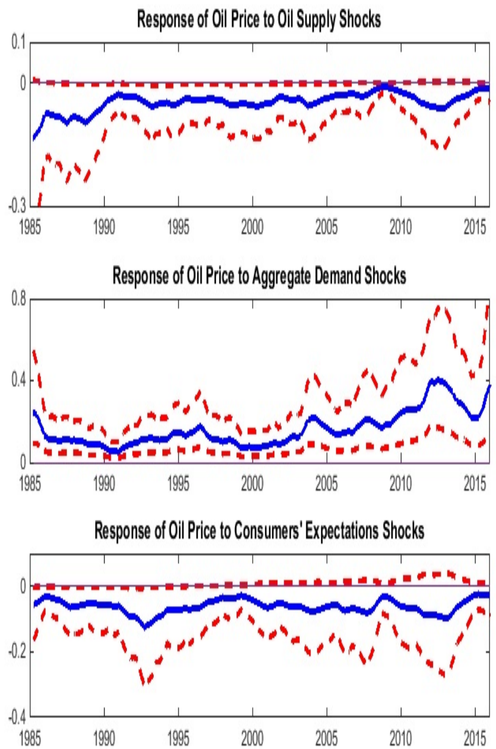


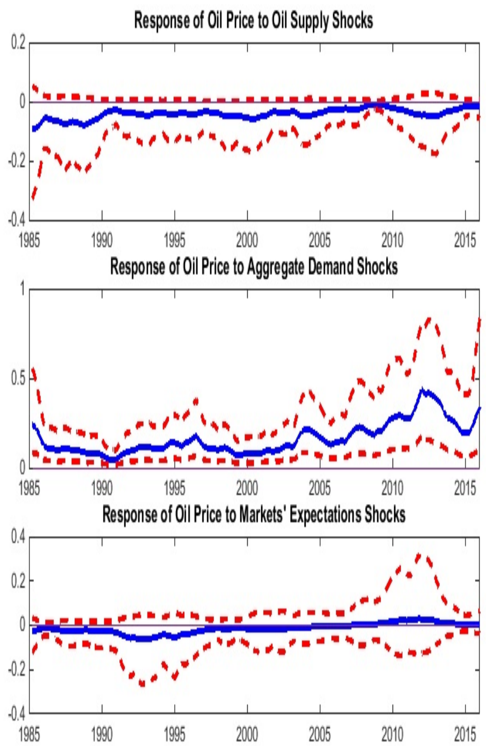
Notes: Each figure measures how a unit impulse of several shocks impacts the oil price over the full sample period. In each panel solid lines represent the median responses whereas dashed lines indicate the $16th$ and $84th$ percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and expectations. The estimates are based on the TVP-VAR model with Stochastic Volatility.

Table B3: Robustness Analysis using US Expectations Indicators

Panel A: Responses of oil prices to fundamentals and business leaders' expectations shocks	**Panel B:** Responses of oil prices to fundamentals and consumers' expectations shocks	**Panel C:** Responses of oil prices to fundamentals and markets' expectation shocks







Notes: Each figure measures how a unit impulse of several shocks impacts the oil price over the full sample period. In each panel solid lines represent the median responses whereas dashed lines indicate the $16th$ and $84th$ percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and expectations. The estimates are based on the TVP-VAR model with Stochastic Volatility.